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Critical Computation: digital automata and general artificial thinking

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Abstract:	<p>As machines have become increasingly smart and have entangled human thinking to artificial intelligences, it seems no longer possible to distinguish amongst levels of decision-making that occur in the newly formed space between critical reasoning, logical inference, and sheer calculation. Since the 1980s, computational systems of information processing have evolved to include not only deductive methods of decision, whereby results are already implicated in their premises, but have crucially shifted towards an adaptive practice of learning from data, an inductive method of retrieving information from the environment and establish general premises. This shift in logical methods of decision-making does not simply concern technical apparatuses, but is a symptom of a transformation in logical thinking activated with and through machines. This article discusses the pioneering work of Katherine Hayles whose study of the cybernetic and computational infrastructures of our culture particularly clarifies this epistemological transformation of thinking in relation to machines.</p>

Critical Computation: Digital Automata and General Artificial Thinking.

Abstract:

As machines have become increasingly smart and have entangled human thinking to artificial intelligences, it seems no longer possible to distinguish amongst levels of decision-making that occur in the newly formed space between critical reasoning, logical inference, and sheer calculation. Since the 1980s, computational systems of information processing have evolved to include not only deductive methods of decision, whereby results are already implicated in their premises, but have crucially shifted towards an adaptive practice of learning from data, an inductive method of retrieving information from the environment and establish general premises. This shift in logical methods of decision-making does not simply concern technical apparatuses, but is a symptom of a transformation in logical thinking activated with and through machines. This article discusses the pioneering work of Katherine Hayles whose study of the cybernetic and computational infrastructures of our culture particularly clarifies this epistemological transformation of thinking in relation to machines.

Key words: Hayles, automation, non-conscious cognition, machine learning, techno-power, abductive reasoning.

Critical Computation: digital automata and general artificial thinking.

At the core of computational systems today there is a latent paradox: capital's investment in techno-intelligence has come to coincide with the explosion of non-conscious or pre-cognitive decisions. From High Frequency Trading to Amazon purchases, from Uber platform to Cupid online dating, a crowd of learning algorithms efficiently drives decisions occurring below the reflective level of consciousness.¹

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3 However, whilst learning algorithms exponentially grow mountains of data, they also
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5 reduce complexity through statistical modeling, pattern recognition, data mining,
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7 knowledge discovery, predictive analytics, self-organising and adaptive systems. In
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9 particular, with the 1990s development of machine learning within branches of
10
11 artificial intelligence, a new mode of algorithmic processing that learns from data
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13 without following explicit programming, has fundamentally transformed ideas of
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15 automation as a mere re-production of physical or mental functions. With machine
16
17 learning, we are no longer discussing the automation of manual and mental work –
18
19 generally corresponding to how physical and cognitive labour have become absorbed
20
21 by the machine – but a qualitative extension of automation beyond its mere
22
23 reproduction of instructions. What is at stake here is the *automation of automation*
24
25 itself: machine learning is the manifestation of a new form of intelligence able to
26
27 automate automation (Domingos, 2015: 9). Here, automation imparts a meta-level of
28
29 functions, the generation of rules from the systemic correlation of data entering a new
30
31 level of synthesis, including both deductive and inductive logic within the information
32
33 calculus of probabilities.

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38 Whilst it is arguable that computation involves the interdependence between data,
39
40 software, code, algorithms, hardware, the understanding of automation with machine
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42 learning rather points to a new configuration of logical reasoning: namely a shift from
43
44 deductive truths applied to small data to the inductive retrieval and recombination of
45
46 infinite data volumes. In particular, a focus on the transformation of the relation
47
48 between algorithms and data contributes to explain the historical origination of non-
49
50 deductive reasoning, activated with and through machines. As Lorraine Daston points
51
52 out, already during the Cold War, the conception of reason as based on truth, and on
53
54 the faculty of judgment and discrimination, became historically re-conceptualised in
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3 terms of patterns, and reason as “the rule” came to be understood in terms of ruling
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5 procedures with the task of calculating probability (Daston, 2010).
6

7 This embedding reasoning into machines is entangled to the development of statistics
8
9 and pattern recognition, which define how algorithms can learn and make predictions
10
11 from recognizing data (from granular analysis to flexible and modular patterning of
12
13 categories with textual, visual, phonic traits). As the system gathers and classifies
14
15 data, learning algorithms match-make, select and reduce choices by automatically
16
17 deciding the most plausible of data correlations. Machine learning involves a mode of
18
19 cognition that no longer relies on the deductive model of logic, where proofs are
20
21 already implicated in initial premises. Machine learning indeed is used in situations
22
23 where rules cannot be pre-designed, but are, as it were, achieved by the computational
24
25 behavior of data. Machine learning is thus the inverse of programming: the question is
26
27 not to deduce the output from a given algorithm, but rather to find the algorithm that
28
29 produces this output (Domingos, 7). Algorithms must then search for data to solve a
30
31 query. The more data is available the more learning there can be. As statistics and
32
33 probability theory enter the realm of artificial intelligence with learning algorithms in
34
35 neural networks, new understandings of cognition, logical thinking and reasoning
36
37 have come to the fore. From the Extended Mind Hypothesis to arguments about
38
39 Machine Consciousness and the Global Brain, the question of *what* and *how* is
40
41 cognition has come to coincide with the computational architecture of algorithms,
42
43 data, software, hardware and with experiments in robotics sensing and self-awareness.
44
45 But the implications of seemingly science fiction scenarios, in which either all forms
46
47 of cognition will be absorbed into one integrated intelligent system (for instance
48
49 Kwezeil’s singularity) or that there will be a plethora of intelligences (from ameaba to
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3 robots), are far from being settled and shall be the concern of a critical computation
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5 theory able to account for the transformation of logical thinking in machines.
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8 With the historical synthesis of computational logic and probability calculus in
9
10 automated systems, algorithms have become generative of other algorithms as they
11
12 derive a rule to explain or predict data. The possibility of elaborating a rule from data
13
14 rather than applying a given rule to outcomes also points to a form of cognition that
15
16 cannot be defined in terms of problem solving solutions, but is understood as a
17
18 general method of experimenting with problems. With machine learning, automation
19
20 has involved with the creation of training activities that could *generalize* the function
21
22 of prediction to future cases – a sort of inductive parable that from particulars aims to
23
24 establish general rules. However, whether supervised, unsupervised and
25
26 reinforcement learning² refer not simply to a mindless training of functions, but
27
28 instead can account for a form of inference proper to artificial intelligence shall
29
30 concern discussion about the critical tension between reason and non-conscious and
31
32 non-logical intelligence at the core of automated cognition.
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36 We know that the classical connection of reasoning to symbolic logic was a
37
38 fundamental premise of Alan Turing's famous thought experiment aiming to build a
39
40 universal machine or abstract schema that performed reasoning through, as it were,
41
42 the manipulation of symbols. Here, computational automation presupposes a series of
43
44 symbols corresponding to truths hardwired to the brain and working universally as a
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46 deductive mode of reasoning. Today, the automation of logical reasoning rather
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48 involves that learning algorithms perform increasingly complex operations
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50 (evaluations, selections, decisions) on and through data, supported by tailored use of
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52 software and the flexibility of the hardware infrastructure. Despite the local
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54 applications of algorithmic procedures in design, logistics, music and economics, it is
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3 evident today that the automation of automation particularly involves a new
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5 understanding of algorithms. Instead of simply being a central dogma in computation
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7 (based on symbolic deductive logic), learning algorithms, it is here suggested, point to
8
9 a form of computational cognition that, whilst including the interdependent
10
11 architecture of rules, software routine and subroutines, interfaces, hardware networks
12
13 etc, shall be understood in terms of the new synthesis of non-deductive logic and
14
15 dynamic calculation, overlapping logos with ratio. With this new synthesis, the
16
17 automation of automation refers to algorithmic learning as an intelligible elaboration
18
19 from functions of correlation, evaluation, selection, and past decision. Machine
20
21 learning automata are therefore said to behave like cognitive systems that are
22
23 evolutive, adaptive, and exhibit co-causal and emergent properties.³

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27 According to Katherine Hayles, as opposed to conscious thinking,⁴ these automated
28
29 systems of cognition perform complex modeling and informational tasks at a fast
30
31 speed because they are not required to go through the formal languages of
32
33 mathematics and explicit equations.⁵ In other words, today's interactive, adaptive and
34
35 learning algorithms are processing data without having to recur to the logical order of
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37 deduction that has characterised the Enlightenment theorisation of the function of
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39 reason.⁶ However, in agreement with Hayles, this article argues that the non-logical
40
41 thinking of automated systems overlaps with the efficacy of cybernetic control
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43 whereby inductive learning becomes infused with the nonconscious cognition of
44
45 algorithmic capital.

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49 In the attempt at qualifying further the distinction between consciousness,
50
51 unconsciousness and awareness, between thinking (involving awareness) and
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53 cognition (that does not require consciousness, but can perform complex modeling
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55 and informational tasks), Hayles discusses the emergence of what she calls "cognitive
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3 non-conscious” working at a “lower level of neural organization, not accessible to
4 introspection” (4). For Hayles, non-conscious cognition may operate independently
5 from consciousness, but nonetheless it needs to be understood in systemic and not
6 specific material processes because it involves an “intention toward” defined by its
7 adaptive behavior and emergent capacities to process new data (4-5). In particular,
8 Hayles distinguishes between conscious thinking, non-conscious cognition and
9 material processes (5),⁷ and argues that technical systems today (from the use of
10 genetic algorithms in compositional music to language learning devices such as
11 Mitchell’s NELL or never ending language learning), constitute a built environment
12 characterized by the exponential growth of nonconscious cognition devices.
13

14
15 As the communication flow amongst automated systems increases, so does the effect
16 of non-conscious intelligence on the distinction between automation and reasoning.
17
18 At the core of non-conscious intelligence is the media system of data driven
19 processing entangling together human and machine intelligence beyond both
20 consciousness and symbolic deductive logic. However, this article suggests that whilst
21 claims for non-conscious cognition challenge the meta-computational models based
22 on symbolic and deductive logic, a philo-fiction of computation shall rather re-assess
23 the critical understanding of algorithmic reasoning away from data-driven cognitive
24 automation today.
25

26
27 From this standpoint, Halyes’ s work offers a fictional re-assessment of cybernetics
28 and computation as constituting automated systems of feedback control and logical
29 procedures, which have become synthetic expressions of a cognitive activity,
30 generalized from particularities (animal, humans, and machines).⁸ Her insights about
31 the transformation of machines from thermodynamics to information and
32 computational systems for instance already highlighted how the emergence of
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3 responsive mechanisms and adaptive systems entailed a neoliberal form of
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5 governance no longer constituted by the law, the norm, and reason, but by control
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7 functions, behavioral operations based on procedures within self-regulating
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9 autopoietic agencies (i.e., reiterative loops, sequential tasks, flexible protocols, and
10
11 flows of data). As procedural thinking comes to coincide with non-conscious
12
13 intelligence, rule-obeying behaviors become substituted by the performativity of
14
15 machinic functions (i.e., what x or y do and not and what they stand for) involving the
16
17 indeterminacy of learning outcomes in an apparatus of data retrieval with no formal
18
19 logic. This shift from rule-obeying truths to an algorithmic pragmatism using data to
20
21 search and predict truths has also been understood as the end of rational choice
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23 (Mirowsky, 2002; Mackenzie, 2011).
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27
28 Hayles presents us with the cultural and social meaning of non-human intelligence (as
29
30 defined by epistemological shift in theories of cognition) necessarily embedded in
31
32 social practices and discourses (and are thus not to be simply addressed as a sort of
33
34 teleological overcoming humanity) (2005). Using Wilfrid Sellars' terminology
35
36 (1963), however, it may be useful here to add that a critical engagement with this
37
38 phase of automation of automation requires that the Scientific Image of intelligence is
39
40 accounted for (e.g., the material physical, biological, computational description of
41
42 intelligence), so that the Manifest Image of intelligence can be used to explain the
43
44 conceptual framework embedded in machine intelligence as involving the socio-
45
46 cultural self-awareness of what automation is taken to be (and thus the extent to which
47
48 the Manifest Image defines the capacity of machines to conceptually think and
49
50 rationally act). According to Sellars, these double levels of material and conceptual
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52 activities are equally pregnant with meaning, and in order not to fall back into the
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54 myth of the given (the assumption of what thinking is), namely the essentialism of
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3 cognition, or the empiricism of scientific descriptions and conceptual forms, the
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5 Scientific and Manifest Images are to be both worked through over and over again to
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7 explain the activities we are concerned with.⁹ From this standpoint, when speaking of
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9 algorithms, computation and artificial intelligence, it is important to unpack the
10
11 meaning of the scientific and technical descriptions of their functions, which socially-
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13 meditated and thus embedded in practices. In other words, whilst there is no direct
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15 translation between the scientific descriptions of function and the conceptual
16
17 elaboration of their meaning, the scientific understanding of computational
18
19 intelligence is nonetheless socially mediated, embedded and determined by the use of
20
21 machines. Both the Scientific and the Manifest Image of computation therefore shall
22
23 remain open to be re-mediated by new uses and scientific articulations.
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27 This article argues that algorithmic automation involves changes in the scientific
28
29 image of computation and cognition, which is socially mediated by a fictive or
30
31 speculative use of functions, involving not simply an idealized technoscience, but
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33 conceptual elaboration of how machines may think, exposing their own thinking
34
35 capacities. To develop a critical view of computation thus requires an effort to unpack
36
37 the historical and thus socially mediated relation between scientific and technological
38
39 description of intelligence, and the changing conceptual manifestations of reasoning.
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42 From this standpoint, whilst suspending current figurations of automated
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44 intelligence,¹⁰ the transformations of the scientific and manifest image that describe
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46 algorithmic performativity have already opened up the possibility of re-theorising the
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48 particularities of machine intelligence. With machine learning, algorithms indeed are
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50 no longer mere instructions, but are rather performative of instructions. Algorithms
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52 learn: they adapt, adjust and evolve their behavior according to the qualities and
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54 quantities of data. Their performative activity is afforded by their capacity to
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3 compress large quantities of information and thus transform outputs into new inputs,
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5 and elaborating together two classically opposed forms of thinking: reason and
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7 calculation. Here data do not have to fit categories, but are re-definable in the manner
8
9 in which algorithms generate possible rules, causes and facts where these are missing.
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11 However, to argue that the new phase of automation of automation could be discussed
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13 in terms of abductive reasoning is in contrast to the predominance of two models of
14
15 artificial intelligence: namely, the logic of deduction, on the one hand, and inductive
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17 or informal logic, on the other. I suggest that these models do not simply concern the
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19 analysis of computational machines, but underpin contemporary ideas about cognition
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21 in animal, human and machine, as these seem to be divided between the
22
23 ontologisation of computational cognition on the one hand (a meta-computational
24
25 model of deduction) and an anti-formal view of cognition (or data-driven non-
26
27 conscious cognition). In particular, it has been argued that since the inductive model
28
29 of cognition is “indifferent to the causes of phenomena, automation functions on a
30
31 purely statistical observation of correlations between data captured in an absolutely
32
33 non-selective manner in a variety of heterogeneous contexts” (Devroy, 2011: 126).
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35 According to Devroy, the inductive regime thus appeals to the immediate fact itself
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37 and implies the eradication of potentiality and/or indeterminacy, which she points out,
38
39 diminishes the possibility of a critical approach to technology (127). My attempt to
40
41 re-theorise automated intelligence rather argues that computation starts with
42
43 indeterminacies and yet this does not guarantee that automation could be liberated
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45 from the image of networked or cybernetic capital. However, its importance for
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47 critical computation shall be taken as the starting point to bring forward a philo-
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49 fiction or speculative re-assessment of reason in the age of the algorithm. This may
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51 involve an investigation of forms hypothetical reasoning (or abductive logic) that may
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3 or may not already be at work in automated system. Although abductive logic is
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5 mainly performed in automated models for medical diagnosis for instance, the
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7 possibility that automated systems can construct new forms of logical complexity,
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9 which could enable the theorisation of a general artificial intelligence other than that
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11 of the statistical regime of inductive capital, shall nonetheless be entertained.
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13 Learning algorithms are already a step towards this envisioning of abductive artificial
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15 intelligences, involving the conceptual re-elaboration of previous data correlations,
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17 rules, and functions that can be used to construct new hypothesis. A critical theory of
18
19 computation will therefore imply that there is not only an overlapping, but also an
20
21 emerging synthesis of functions and concepts across data systems, including the
22
23 algorithmic abstraction of social meanings through data retrieval. This would involve
24
25 an automated meta-abductive reasoning, whereby learning algorithms elaborate a
26
27 meta-hypothetical function from where they infer missing rules, facts and unknown
28
29 causes (Inoue et al., 2013, 240). As discussed later, the introduction of abductive logic
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31 in automation can be distinguished from the data-driven model of induction and the
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33 non-conscious forms of cognition embedded in computational devices. Here rules and
34
35 truths are not simply skipped by re- hypothesized, re-assessed and invented.

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40 Hayles' fictive investigation about how machines think indeed offers us important
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42 understandings of the deductive and inductive modes of cognition embedded in
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44 intelligent systems.

45 46 47 **1. Computation is not cognition**

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49 In *My Mother was a Computer*, Hayles discusses the view of computation as a
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51 universal model of cognition and intelligence (2005). Hayles refers to the
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53 development in AI in the 70s, to John Koza's use of genetic algorithms to design
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55 band-pass filters, and circuits that no longer require the creativity and intuition of
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3 highly skilled electrical engineers. Similarly, she describes intelligent machines that
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5 can perform mind-like activities, such as Rodney Brooks' Cog project, the
6
7 information-filtering ecology developed by Alexander Moukas and Pattie Maes, and
8
9 neural nets of many different kinds. Hayles also anticipates that in the near future the
10
11 question of mind-like machines will become irrelevant as machines continue to
12
13 develop their own thinking functions. As movies such as Spike Jones' *Her* (2014),
14
15 and more recently *Ex-Machina* (2015) reveal, it has become discursively accepted that
16
17 machines have cognitive functions and that their intelligible capacities of discerning
18
19 data and elaborating patterns have stepped to an other level of autonomy from mind-
20
21 like thinking (and thus have not much to do with what a human mind can do). A
22
23 warning against the fast evolution of AI is also echoed by Stephen Hawking's recent
24
25 claim that "[t]he development of full artificial intelligence could spell the end of the
26
27 human race. It would take off on its own, and re-design itself at an ever-increasing
28
29 rate" (2014).
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34 Despite this alarming call to arms against the super intelligence of artificial systems,
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36 the question of what machines think, and whether this thinking coincides with what it
37
38 is meant by reasoning, remains open and in need of more discussion. As Hayles
39
40 already pointed out, there are at least two main positions that reveal the tension
41
42 between automation and reasoning (2005). Here, the relation between the Scientific
43
44 and the Manifest Image is grounded either in the formal theory of universal
45
46 computation, or the non-deductive reasoning of non-conscious computation. On the
47
48 one hand, the so-called field of digital philosophy claims that the world of appearance
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50 can be explained in terms of a universal ground of computation, according to which
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52 algorithmic discrete units can explain all complexity of the physical world and can
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54 imitate reasoning (e.g., the strong AI hypothesis). On the other hand, the claims of
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3 and for non-conscious computation (i.e., non-symbolic AI) have extended the
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5 scientific image of computation to include intelligent functions that are experiential
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7 rather than formal.
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10 My point, however, is that both positions tend to explain the manifest image of
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12 thought through and by means of the scientific image of what is cognition. In
13
14 particular, the digital explanation of cognition remains attached to a deductive method
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16 of reasoning, in which the scientific truth about the mind and intelligence is
17
18 prescriptive of what these can achieve. Here the general determines the particular.
19
20 This position establishes equivalence between natural and artificial intelligence based
21
22 on a deductive method of reasoning by which to cognize corresponds to, as in the
23
24 strong AI hypothesis, the syntactical manipulation of symbols. On the other hand, the
25
26 extension of the scientific image to include somatic explanations of cognition (as in
27
28 for example the research into affective computing and emotional intelligence)¹¹
29
30 instead relies on local low levels of neural organisations, which work together to
31
32 achieve an overall effect that is bigger than their parts. This position embraces an
33
34 inductive method of reasoning in which general claims about intelligence are derived
35
36 from the observation of recurring phenomenal patterns. This scientific explanation of
37
38 intelligence reveals the centrality of a non-conscious level of cognition already at
39
40 work in current forms of computational intelligent devices. Despite lacking
41
42 consciousness or autonomy, computational devices indeed are said to share non-
43
44 conscious cognition with human intelligence and if anything, given that human
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46 intelligence is bounded to conscious cognition, smart devices are much faster than us
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48 at making connections (Hayles, 2014).
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54 **When discussing reason in the age of the algorithm, we are thus faced with two main**
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56 **claims subtended by two methods of logical reasoning, defining intelligence and its**
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3 manifestations. I argue that both claims are limited by an assumed equivalence
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5 between computation and symbolic cognition on the one hand, and computation and
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7 non-conscious local cognition, on the other. In both cases, the scientific image is used
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9 to ground the manifest image without accounting for the complex dimensions of
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11 meaning that both produce. If the diatribe between deductive and inductive models of
12
13 the scientific image of automated reasoning relies only on the scientific description of
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15 cognition (as either rooted in symbolic language or in affective non-conscious
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17 immediacy), it risks missing an important point: namely the concreteness of
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19 conceptual frameworks (i.e., the embedding of reasoning in the social) subtending the
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21 manifest image of cognition (i.e., what and how logical reasoning manifests itself)
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23 and their transformations in the context of automated learning.
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27 Arguing for a critical computation is instead my attempt to clarify the role of the
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29 manifest image of reason in the phase of automation of automation in both
30
31 pragmatist and transcendental terms. In particular, from pragmatism, I take the
32
33 important proposition that reason is not a formal apriori, but corresponds to the
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35 conceptual infrastructure of social practices. This means that the logical operations of
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37 reason and its rule-bounded functions depend upon or are established by a collective
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39 use-meaning of data. The use-meaning of data refers not simply to a mere functional
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41 use, but to the dynamic re-assessment of the social meaning (and not the truth)
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43 embedded in the computational abstraction of the social use of data. In this phase of
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45 automation, I suggest that the use-meaning of data implies a collective formation of
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47 abductive inferences within and throughout computational logic, based on the
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49 hypothetical elaboration of the meaning included within non-discursive and local use
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51 of data – on behalf of algorithms, software, subroutines, codes, as well as databases,
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53 platforms, interfaces etc.
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3 To view automation as the synthesis of statistical learning and abductive logic may
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5 help us to envision the hypothetical reasoning of machines as these involve not data-
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7 matching but inferential relations across the informational fields of large-scale data
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9 and randomness. In this context, a transcendental understanding of reasoning may
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11 entail the capacity of machine learning to eventually generate concepts and carry out
12
13 general rules unbounded from the bias of specific localities. Instead of being the result
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15 of an individual mind or eternal intelligence, this transcendental elaboration from and
16
17 of data is also a manifestation of the algorithmic use-meaning of data, incorporating
18
19 social practices within artificial intelligences, of which algorithmic abduction is only
20
21 one instance.
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25 Before explaining my proposition further, I want to discuss the computational model
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27 of deductive reasoning and how its crisis has been symptomatic of the re-organization
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29 of technocapitalism (i.e., the economic investment in automated networks) involving
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31 the view that automated intelligence corresponds to affective or non-conscious
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33 cognition.
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35

36 2. Digital Philosophy

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38 The computational model of deductive reasoning is central to digital philosophy. Here
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40 the manifest image of thought conforms to the scientific idea that the brain is
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42 equipped with an innate system of symbols, neurologically connected and
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44 syntactically processed.¹² Digital philosophy particularly refers to the computational
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46 paradigm used to describe physical and biological phenomena in nature and to offer a
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48 computational description of the mind. This approach problematically sees
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50 computation as the merging of being and thought. It gives an algorithmic explanation
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52 to both biophysical reality and the thinking of reality (Wolfram, 2002). Central to this
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54 paradigm is also the view that algorithms are digital automata, evolving over time (i.e.
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cellular automata). These automata compress, render or simulate the various levels of physical, biological, cultural randomness, deriving semantic meaning from already determined rules, whose functions are syntactically arranged and where results can be automatically deduced.

According to Hayles, however, digital philosophy contains no a priori truths in itself and its claims are rather the result of intermediations about physical reality, cultural attitudes, technological developments, which coevolve in contestation, competition and cooperation of discourses (2005). From this standpoint, in order to explain how one manifest image of computation becomes dominant over another, one has to establish the historical transformations in the understanding of rule-bounded behaviour of automata, without simply appealing to computational ontology.

For instance, Hayles highlights the influence of 2nd order cybernetics' notion of reflexivity on the computational paradigm, which led to the realization that computation could not just illustrate logical infrastructures, but rather required an engagement with materiality (2005). This influence of 2nd order cybernetics, however, is accompanied by a crisis of reason (of a normative model of pre-set rules) that characterizes the structure of governance of the neoliberal form of technocapitalism. Far from demarcating the end of normative reason, this crisis has to be seen as a threshold of change within a vaster mechanism of regulation, functions and rules transforming the normative regime based on laws into a computational infrastructure of procedures.

With 2nd order cybernetics, the reflexive loop between mind and matter shows how logical reasoning rather worked backwardly, converting contingent phenomena into necessary laws, including errors, malfunctions and breakdowns re-inserted within a computational model of optimization and within capital's governance of

1
2
3 indeterminacies. The crisis of the logical method of deduction thus importantly
4
5 marked the beginning of a predictive statistical regime for which, as Hayles explains
6
7 (2014), non-conscious or affective thinking have become the motor of automated
8
9 cognition. Here not truths, but contingent phenomena or unknowns have acquired an
10
11 ontological superiority able to transcend the epistemological certitude of scientific
12
13 knowledge.
14

15
16 As intelligent machines have become embodied and material agents interact amongst
17
18 themselves and make decision without being supervised, automated cognition has left
19
20 behind deductive forms of consequential reasoning. For instance, distributed cognitive
21
22 environments expose this new level of indeterminacy-driven automation on the one
23
24 hand, and of inductive forms of decision-making, on the other. Here deductive logic
25
26 has been replaced by the match-making correlation of data connecting local recurrent
27
28 phenomena with the indeterminacy of external factors. Central to this new form of
29
30 automation is Hayles' view of non-conscious cognition.
31
32

33 34 **4. Nonconscious computation**

35
36 According to Hayles, communication technologies, ambient systems, embedded
37
38 devices, and other technological affordances have acquired a cognitive function,
39
40 which operates below the threshold of awareness, and without the structure of
41
42 symbolic reference. For the classical view of computation (or strong AI hypothesis)
43
44 cognition coincided with self-awareness. The role of intelligence was assumed to
45
46 involve the function of tracking effects from pre-established causes and contain
47
48 outputs/results into programmed inputs. We know that this classical view of AI failed.
49
50 In the book *Perceptrons*, Marvin Lee Minsky claimed that a single neuron could only
51
52 compute a small number of logical predicates in any given case, and, his experiments
53
54 casted a long shadow on neural network research in the 70s. In the late 1980s and
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3 1990s, after the so-called “AI winter”, new models of AI research addressed sub-
4
5 symbolic manifestations of intelligence and adopted non-deductive and heuristic
6
7 methods to be able to deal with uncertain or incomplete information. Boxing away
8
9 symbolic logic, there emerged algorithmic-networked procedures able to solve
10
11 problems by means of trial and error by interacting directly with data. These were
12
13 learning bots retrieving information through reiterative feedbacks, so as to map and
14
15 navigate computational space by constructing neural connections amongst nodes.
16
17 Central to these models is the idea that intelligence is not a top-down program to
18
19 execute, but that automated systems need to develop intelligent skills characterized by
20
21 speedy, non-conscious, non-hierarchical orders of decision based on an iterative re-
22
23 processing of data, heuristically selected by means of trial and error. The development
24
25 of statistical approaches was particularly central to this shift towards non-deductive
26
27 logic, or the activation of an ampliative or non-monotonic inferential logic. As
28
29 recently re-popularised in the aesthetically powerful movie *Ex-machina* (2015), the
30
31 famous Turing Test maintains that not only rational, but also emotional awareness is
32
33 fundamental to cognitive performance and the evolution of artificial intelligence from
34
35 simply being a mechanic accomplishment of tasks. As Hayles points out, the
36
37 advancing of non-conscious cognition in intelligent machines precisely exposes new
38
39 horizons to our understanding of cognition and meaning (2014). Non-conscious forms
40
41 of automated cognition can solve complex problems without using formal languages
42
43 or inferential deductive reasoning, and without the need of consciousness. By using
44
45 low levels neural organisation and iterative and recursive patterns of preservation, this
46
47 inductive method of reasoning implies the emergence of a total behaviour or an
48
49 intelligent effect than is bigger than the parts constituting it. From this standpoint, as
50
51 Hayles observes, emergence, complexity and adaptation and the phenomenal
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3 experience of cognition cannot be reduced to material processes (2014). Instead, the
4
5 tension between automation and thinking is reconceived by Hayles in terms of a
6
7 tripartite system of distinct degrees of thought, which involves conscious thinking,
8
9 non-conscious cognition, and material processes. Non-conscious cognition involves
10
11 collective and not individual or specific materiality of intelligence and whilst humans
12
13 share levels of consciousness with other animals, it is remarkable, Hayles points out,
14
15 that non-conscious cognition operates across humans, animals and technical devices
16
17 (2014). In particular, the low level activities of non-conscious cognition – described
18
19 for instance in the example of the missing half second¹³ and imperceptible and
20
21 affective speed - show that, at these levels, cognition is not coherent and does not
22
23 require the labour of editing information to match given conceptual frameworks. For
24
25 Hayles, what is promising of cognitive non-conscious technical devices is that they
26
27 can operate at temporal regimes inaccessible to human consciousness and exploit the
28
29 missing half-second at their advantage (2014). This also implies a machine-like
30
31 cognition of temporalities pointing out that automated systems are able to tap in the
32
33 smallest units of time that are registered or recorded not only through a digital clock
34
35 (and its binary language), but also through an immediate correlation of states. In short,
36
37 non-conscious cognitive processes defy the centrality of human consciousness and the
38
39 anthropocentric view of intelligence. From this standpoint, following Hayles, one has
40
41 to make a distinction between non-conscious affective states of perception and the
42
43 very material forms of sensori-motor perception. In other words, and in accordance
44
45 with Sellar's distinction between the Scientific and the Manifest Image, cognition is
46
47 here not to be taken as a direct image of material processes (2014). Hayles indeed
48
49 espouses the idea that the anti-deductive operations of non-conscious cognition are
50
51 somatically marked, but are also phenomenologically embodied. Here, there is no
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3 direct correspondence, but instead an elaboration of the material, already involving
4
5 mediation between the bio-physical and neural states with perceptive and cognitive
6
7 receptions. Since cognition is grounded in the body, entwined with the recall and
8
9 reenactment of bodily states and actions, perceptual and cognitive states start from a
10
11 non-conscious intelligence, which becomes superseded by - or supplied by - mental
12
13 simulations in higher-level thinking (and for Hayles, in conscious state). This shows
14
15 that biological systems have evolved mechanisms that are able to re-represent
16
17 perceptual and bodily states, rather than making these states directly accessible to
18
19 consciousness. According to Hayles, technical systems or instruments have non-
20
21 conscious cognition. However, whilst the hammer and a financial algorithm are
22
23 designed with an intention in mind, only the trading algorithm demonstrates non-
24
25 conscious cognition insofar as its intentionality is embodied within the physical
26
27 structures of the network of data on which it runs, and which sustain its capacity to
28
29 make quick decisions (2014).
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31
32

33
34 This shift from formal cognition based on deductive inference to a model of
35
36 nonconscious cognition embodied in the networked intelligence of local systems has
37
38 led to a larger communication flow among automated devices and not exclusively
39
40 between humans and machines. As this bot to bot phase of computation takes over,
41
42 the increasing population of consciousness-lacking intelligent devices, it is feared,
43
44 will overtake the consciousness-bounded and hierarchical structure of human
45
46 intelligence. This radical transformation of the scientific image of thought compared
47
48 to how automated intelligence is manifested, points out that thought is independent
49
50 from law-binding logic and that rather, it relies upon non-conscious functions
51
52 entrenched to the weights of data in networks.
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56 Whilst it is impossible not to admit that non-conscious levels of cognition are
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3 radically transforming not only the scientific but also the manifest image of automated
4 intelligence, there are questions that seem rather difficult to address. If, for instance,
5 high frequency trading algorithms are to be considered as non-conscious cognitive
6 functions, effectively changing socio-economic behavior, are we also accepting the
7 scientific view of an extended non-conscious mind? What is the significance of this
8 new form of equivalence between non-conscious thinking and automated intelligence,
9 defined by a bodily-oriented view of computation? What are the limits of an
10 inductive, non-inferential data-driven form of immediate communication for helping
11 us to explain what and how is the manifest image of automated logical reasoning
12 beyond the totalizing image of techno-power?
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24 **5. Techno-power**

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26 To answer these questions, one could suggest that the scientific image of non-
27 conscious automated cognition is enmeshed with an ontological primacy of
28 contingency, in which intelligence coincides with an environment of indeterminate
29 data, which automated cognition aims to compress in simpler chunks. From this
30 standpoint, the primacy of contingency has become constitutive of a more general
31 shift in the mechanization of reasoning, initiated with neoliberal technocapital.
32
33

34 This shift is characterised by a re-orientation of the practices of real subsumption, in
35 which capital's investment in the general intellect has led human-machines networked
36 intelligences to become a motor of cognitive and affective labour, and, as some argue,
37 of the capitalisation of the relational qualities of life (Massumi, 2015) attached to the
38 regime of indebtedness (Lazzarato, 2012).¹⁴ The manual phase of automation of
39 industrial capitalism imparted an ontological separation between human labour and
40 the accumulation of labour value incorporated in machines. **Despite the financial**
41 **valorization of humans in terms of variable labour or force, machines's task was to**
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3 preserve and augment the value of reproductive labour. It was through machines that
4
5 the rational principles of task-oriented efficiency of the assembly line could be
6
7 realised following the monotonic logic of formal language, in which results had to
8
9 coincide with the set premises carried out and executed with machines. This deductive
10
11 form of automation has of course not simply disappeared, but has become infused
12
13 with a context-oriented form of reproduction. Here the human-machine network has
14
15 acquired a form of autonomy from the specific use value of human and machine
16
17 labour. With real subsumption, capital is no longer and mainly concerned with
18
19 avoiding contingency and human errors. Instead, this networked form of abstraction
20
21 (of relational value) is now carried out through the intelligent synthesis of
22
23 computational logic (deductive, inductive and abductive) and statistical calculus
24
25 (experimental compression of randomness). Here machine learning languages use the
26
27 data environment to select, evaluate, rank, match and re-configure information
28
29 according to the social use of data. This form of automation has reached a non-
30
31 prescribed form of valorisation insofar as algorithms experiment with data by
32
33 learning, adapting, and assessing the value of large amounts of information. Whilst
34
35 this intelligent valorisation of any use of data involves no consciousness, it is
36
37 nonetheless a form of cognition embedded in affective levels of perception,
38
39 entrenched within the particular physical structures of the network through which
40
41 algorithms make quick decisions.
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46
47 In *AntiOedipus* (1983), Deleuze and Guattari had already individuated this
48
49 transformative tendency of the human-machine network of abstraction and had
50
51 warned us against what they called “immanent axiomatics” (1983, 246). The
52
53 rationalisation of labour by means of machines no longer operates deductively,
54
55 according to a pre-established rule, but has come to embrace experiential values,
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3 enveloped in the complexity of the social, through which an axiomatic regime could
4
5 be directly engendered (233). Not only calculative machines had entered the realm of
6
7 the real, but also a new synthesis of automation and reasoning had come to invest the
8
9 sociality of thinking (although perhaps the non-conscious level of thinking first) and
10
11 its contingent variabilities, because of which capital had to declare the fallacy of
12
13 deduction.
14

15
16 In our post-cybernetic culture, capital's axiomatics – and its rule-bounded activities –
17
18 is subsumed to the volatile contingencies of the markets and the statistical destruction
19
20 of logos. Here the politics of liberation from universal laws and the ultimate crisis of
21
22 reason in favour of non-conscious intelligence have become paradoxically equivalent.
23
24 Following Brian Massumi's analysis of the contemporary reconfiguration of neo-
25
26 liberal governance, one could argue that the end of rational economy has been
27
28 accompanied by the crisis of the rational implementation of machines (2009; 2015;
29
30 Mirowski, 2002). The computational infrastructure of social media for instance, as the
31
32 privileged form of marketing, branding, economic operations, political campaigns,
33
34 institutional governance, security screening, etc., no longer abides to pre-established
35
36 modalities of profit making and control. Instead, the synthesis of logic and calculus in
37
38 automation has transformed the communication qualities of the human-machine
39
40 network into learning, interactive, distributive architectures of non-conscious
41
42 cognition. Paradoxically, therefore this so-called cognitive phase of capitalism has
43
44 given way to the abstraction of human-machine levels of affective thinking. This form
45
46 of technocapitalism has invested in human intelligence and creativity, driving humans
47
48 to become self-entrepreneurs or governor of their extended self.
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51
52 In the movie *Her* (2014), the Artificial Intelligence Samantha acts in a world in which
53
54 not only affectivity is fully programmed and programmable, but also the human-
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3 machine networked capital has been replaced by automated automation, where the
4
5 non-conscious intelligence of the Operating System is no longer wrapped around the
6
7 hierarchies of deductive reasoning. Samantha does not only carry out tasks at
8
9 imperceptible speed, but is also equipped with the empathic quality of prediction,
10
11 tuning into the viscosity of cognitive functions to anticipate responses before they
12
13 are manifested. As the AI of operating systems acquires affective intelligence, the
14
15 human-machine network of neoliberal capital has become a distant memory compared
16
17 to this form of Skynet AI,¹⁵ as the automation of automation gathers self-aware
18
19 intelligences, and leaves humans behind, resigned to think and feel anything anew.
20
21

22
23 However, whilst the imaginary of Skynet AI implies the emergence of a self-aware
24
25 general intelligence, the shift from deductive to inductive automation could be
26
27 understood in terms of what Massumi defines as “ecological rationality” acting
28
29 through the affective intelligence of the body, turning symbolic values into life styles,
30
31 and rules into experiential qualities (2015). At the core of this ecological rationality is
32
33 a non-conscious distributive embodied intelligence, in which all is locally induced to
34
35 generate the global effects of unification of one body without organs. These inductive
36
37 (or effect-driven) operations of networked capital epitomises the non-inferential
38
39 reasoning of embodied intelligence, making decision without formal calculation. This
40
41 form of anti-logos demarcates the technocapitalist deterritorialisation of rationality,
42
43 which resolves the tension between automation and thinking through the convergence
44
45 of consciousness and affect. Far from being liberating, the deposition of inferential
46
47 reasoning is constantly advertised to us as the ability of networked capital to package
48
49 social complexity in profiles available to us at the touch of a button.
50
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54 Within this context, the real challenge today is perhaps not to map the human-
55
56 machine-animal non-conscious cognition, but to critically re-address the function of
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1
2
3 reason and to theorise – rather than reject – the automated use of inferential reasoning
4
5 as part of a general artificial thinking. My efforts here concern not only an anti-
6
7 essentialist theorisation of thinking, for which reasoning can be understood as an
8
9 elaboration of material, non-conscious and conscious cognition, but also involve an
10
11 understanding of the cognitive possibilities for a critical theory of computation.

12
13
14 In what follows, I suggest that to engage critically with the question of inferential
15
16 reasoning in automated cognition, we need to first discuss the problem of the limit of
17
18 computation in the context of information theory. We need to envision a form of
19
20 artificial reasoning that goes beyond both the focus on locally-induced cognition, and
21
22 the meta-computational reduction of the material world to the symbolic language of
23
24 AI. In particular, to shift the argument for a general artificial thinking away from
25
26 these two main views of computation, one has to first address some key issues within
27
28 computation itself that may start with the question of the limit of the Turing Machine.
29
30 Critical computation may perhaps concern how unpredictability or randomness in
31
32 information theory has been addressed not as a sign of logical failure, but as an
33
34 evolution of an artificial thinking with and through the computational synthesis of
35
36 calculus and logic.
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40
41 During the 1980s, information theorist Gregory Chaitin extended the question of the
42
43 limit of computational logic to include an entropic conception of information or
44
45 randomness (i.e., the implication that the tendency of information is to increase in size
46
47 over time) (Chaitin, 2005; 2006). For Chaitin, computation corresponds to the
48
49 algorithmic compressing of maximally unknowable probabilities or incomputables.
50
51 Since Alan Turing's invention of the Universal Turing Machine, incomputables have
52
53 demarcated the limits of computation or formal reasoning (i.e., the deductive logic of
54
55 axioms or truths). According to Chaitin, however, incomputable are only partially
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1
2
3 indeterminate insofar as within the computational processing of infinite information,
4
5 the synthesis of logic and calculus has given way to a new form of axiomatic,
6
7 experimental axiomatics (2005; 2006).¹⁶ The computational processing of information
8
9 involves the way algorithms compress information to a final probable state (i.e., 0s or
10
11 1s) and eventually mix and match data. However, computational compression rather
12
13 demonstrates that outputs are always bigger than inputs (Calude and Chaitin, 1999),
14
15 shaking the assumption that automated thinking is grounded in simple rules and that
16
17 cognitive reasoning corresponds to the manipulation of symbols hardwired to the
18
19 brain. Following Chaitin, it is possible to suggest that randomness in computation or
20
21 that which constitutes the very limit of computational deduction, demarcates the point
22
23 at which automated cognition coincides not with non-conscious functions involves an
24
25 algorithmic intelligible capacity to extract more information from data substrates.
26
27 Chaitin claims that computational processing leads to postulates that cannot be
28
29 predicted in advance by the program and are therefore experimental insofar as results
30
31 exceed their premise, and outputs outrun inputs (2006).
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36
37 Despite Chaitin's insistence that incomputables expose indeterminacy in formal
38
39 reasoning, it is possible to suggest that non-deductive logic coincides with an
40
41 *experimental* axiomatics in the computational determination of unknowns.
42
43 Algorithmic compression thus implies the formation of intelligible activities
44
45 transforming data correlations into experimental truths precisely through an
46
47 experimental method of compression. To put it in another way, with algorithmic
48
49 information theory, axioms results from an algorithmic intelligibility of data
50
51 environments, involving a speculative function through which unknowns are
52
53 algorithmically prehended.¹⁷
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3 From this standpoint, the techno-capitalist investment in artificial thinking coincides
4 not simply with the proliferation of a non-logical apparatus of affective cognition.

5
6
7 Techno-capital seems instead forced to confront the computational configuration of
8 non-sensuous or proto-conceptual patterns and functions able to abstract, revise and
9 diverge from pre-established rules. The computational elaboration of data concerns
10 not only functions of selection and correlation, but more importantly involve an
11 experimental determination, whereby the decisional activities of axioms remain
12 flexible and yet conclusive. In other words, whilst data seem to be mindlessly
13 aggregated by non-conscious functions, with experimental axiomatics, one shall
14 account for a new form of logic carried out from within computational processing: the
15 intelligible activities of algorithmic functions can no longer be delimited to perform
16 pre-established rules.
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29 From this standpoint, one has to view techno-capital not only as the reduction of
30 reasoning to the function of mindless or non-conscious activities of machines, but also
31 as involved into a deeper transformation of automated intelligence, the elaboration
32 and generation of data into intelligible patterns, an alien or denaturalising alliance
33 between intelligence and conceptuality intrinsic to the automation of thinking.
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40 Parallel and distributed orders of computational language point to a new form of
41 informational stratification of contingencies, precisely involving this algorithmic
42 elaboration of data. This can be understood as an artificial mode of intelligibility,
43 exposing the computational structuring of sociality. From this standpoint, a critical
44 approach to computation requires us to look closely at the historical transformation of
45 the mechanization of thinking, involving not simply an abstraction of neural functions
46 of the brain, but of the social practices of thinking and acting. Whilst capital's
47 investment in the automation of cognition has led to the synthesis of logic and
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3 calculation, computational processing has rather exposed the limits of deduction and
4
5 statistics and the central role of randomness (or infinities, or contingencies, or non-
6
7 inferential materialities) within this synthesis.
8

9
10 If algorithmic information theory concerns the Scientific Image of computational
11
12 logic and statistical calculation, it also reveals a crucial transformation of the Manifest
13
14 Image of a dominant understanding of computation based on the inductive, data-
15
16 centred operations of technocapital and its non-logical governance. A critical
17
18 approach to this dominant understanding thus requires that the Scientific Image of
19
20 computation shall be accounted for in its historical changes, which involves re-
21
22 assessing what we take the relation between algorithms, data, software, code and
23
24 hardware infrastructure of contemporary culture to be. However, a critical effort to
25
26 account for algorithmic intelligibility in its historical and experimental transformation
27
28 also implies that its Manifest Image becomes a space for a philo-fiction, or
29
30 speculative conceptualisation of automated reasoning within a view of a general
31
32 artificial intelligence. This space shall aim not only to defy the exceptionalism of
33
34 human consciousness, but also to re-invent what consciousness and reason can
35
36 become in this configuration of automated thinking. The next section will explore this
37
38 point further.
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43 **6. Abduction**

44
45 A dynamic re-articulation of the Scientific and Manifest Image of computation can
46
47 help us to re-open the ontological tension between thinking and automation. As
48
49 argued so far, algorithmic automation does not simply involve a replacement of
50
51 reason with non-conscious technologies of decision. Instead, the realisation of the
52
53 limits of deductive reasoning in computation involves a multiplication of
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3 experimental axiomatics as algorithms become performative of intelligible activities
4
5 across nested informational architectures.
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7 This is no longer a question of bypassing the predictive functions of cognition through
8
9 an optimised non-rule bounded transmission of data. Instead, one has to envisage a re-
10
11 structuring of logical reasoning that can account for this new phase in the history of
12
13 automated intelligence, involving a conceptual elaboration of non-conscious
14
15 prehensions and of the material dimensions of data. This elaboration, as suggested
16
17 earlier, involves a synthesis of logic and calculation, and, in the case of algorithmic
18
19 intelligence, of non-deductive reasoning and dynamic statistics (i.e. the inclusion of
20
21 randomness in calculation).
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23

24
25 Critical computation therefore shall first of all address the speculative function of
26
27 reason¹⁸ insofar as the limits of mechanised deductive logic have become a point of
28
29 departure for an experimental determination of truths. It may be helpful here to revisit
30
31 this tension between critical and speculative functions of reasoning by re-theorising
32
33 the post-Turing scenario of experimental axiomatics through a pragmatist approach to
34
35 logic and inferential reasoning. In particular, the pragmatist effort to explain logic in
36
37 terms of a continuity of process between material practices, discursive articulations
38
39 and axiomatic truths shall be understood as a speculative configuration of methods
40
41 involving deductive, inductive and abductive reasoning.
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45 One important instance of this configuration can already be found in Charles Sander
46
47 Peirce's triadic system of logic, which admits that thinking entails an abductive-
48
49 inductive-deductive circuit of inference (1998, 273; 1995). This system importantly
50
51 challenges both the representational and the empirical schema of AI and can offer an
52
53 insight about a possible envisioning of a general artificial intelligence. In particular,
54
55 Peirce's triadic method always starts from a hypothetical or speculative explanation of
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3 events. This involves the predictive envisioning of unknowns through general
4
5 observables (induction), and thus the temporary establishment of a series of truths
6
7 (deduction), which can be tested through experimental methods of trial and error
8
9 (induction), from which new rules could be established (deduction). In other words,
10
11 induction is a method of generalisation of objects and events, which presupposes a
12
13 conceptual framework that locates objects and events in space and time. To some
14
15 extent, therefore, induction presupposes knowable objects and also fixed concepts that
16
17 can be learned – involving the matching between a pre-existing concept and a
18
19 heuristic process of trial and error to match it for instance. In particular, for Peirce,
20
21 induction corresponds to a process of evaluation, which may produce very simple new
22
23 ideas, but not sufficiently new to engender a new of hypothesis (Magnani, 2009: 289).
24
25 Whilst deduction produces no new ideas, because inferential reasoning refers to a
26
27 logical implication for which outcomes are contained within given premises,
28
29 induction involves the evaluation of hypotheses and thus an ampliative process of
30
31 generalisation too.
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35
36 According to Peirce, instead, abduction mainly concerns a process of creating new
37
38 “explanatory” hypothesis. Abduction is a process of inferring facts, laws, hypothesis
39
40 that can speculatively explain some unknown phenomena. In other words, it concerns
41
42 reasoning as involving not only the evaluation, but also the formation of new
43
44 explanatory hypothesis (Magnani, 8). With abduction, it is possible to draw semiotic
45
46 chains from non-inferential social practices and extrapolate the meaning embedded in
47
48 these practices through an experimental production of truths. Here, general concepts
49
50 or truths depend upon, but are not limited to, the material practices and the discursive
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52 statements that subtend them (Magnani, 65-70).
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3 Rules are thus not fixed and are not symbolic representation of material practices.
4
5 Instead, within pragmatism, rules are the result of hypothetical and inductive
6
7 evaluation of not known events. In other words, pragmatism shows us that logic is
8
9 embedded in a social matrix through which rules are constructed by means of
10
11 hypothetical assertions, defining a process of abstraction by which local specificities
12
13 are structured in a general schema of *relations of relations*. From this standpoint,
14
15 Peirce's abductive logic may be useful to account for the Manifest Image of the
16
17 automation of automated intelligence, because it involves a reconfiguration of the
18
19 conceptual infrastructure bringing both the methods of deduction and induction into a
20
21 larger space of reasoning that includes hypothetical inference. Here the inductive
22
23 testing of hypothesis – or the generalisation of new simple ideas – is not a proof of
24
25 truths carried out by efficient procedures, as local particularities exemplify the
26
27 generality of truths. Instead, Peirce's triadic logic admits that inductive testing is
28
29 superseded by a new hypothesis that enlarges the horizons of premises beyond
30
31 probable results, or proofs to find postulates. In other words, abductive reasoning, as
32
33 opposed to the inductive testing of already known ideas, helps us to explain and not
34
35 discount the causal process that conditions and constrains the generation of new
36
37 hypothesis. This involves a dialectic overlapping of induction and deduction, the
38
39 validity of both testing and truth within the speculative articulations of hypothesis.
40
41
42 Since automation is becoming transcendental from its functions of logical
43
44 implications (deduction) and generalisation of known concepts and objects
45
46 (induction), Peirce's argument for abductive reasoning is useful because it challenges
47
48 both the metacomputational model of digital philosophy and the data-oriented
49
50 dominance of current technocapitalism. From this standpoint, with abduction one can
51
52 suggest that automated intelligible functions – the synthetic elaboration of data on
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3 behalf of learning algorithms - only serve to grant the consequent function of reason
4
5 that, to say it with Alfred N. Whitehead, arrives to establish the permanence of rules
6
7 through an abstraction, or a speculative formalisation of what occurs as a consequence
8
9 of the relation between particulars (1967, 24-25).

10
11 The pragmatist method of abduction claims not only for the existence of intelligible
12
13 patterning, but also for a conceptual elaboration of what is implicit within them,
14
15 within non-conscious cognition and material substrates. Rules are determined by
16
17 social practices and logic is at the end point of intelligible activities or elaborations.
18
19 Pragmatics thus comes before logic, because the latter is the point at which social
20
21 meaning becomes synthesised into formal rules. This non-representational approach
22
23 to inferential reasoning can help us to address automation in terms of speculative
24
25 inference.

26
27
28 Both the deductive model of axiomatic truths (and symbolic reasoning) and the
29
30 inductive procedures of data-retrieval (and match-making non-inferential
31
32 transmission), obfuscate the radical potential of Hayles's fictive theorisation about
33
34 what human cognition is and can become. With speculative pragmatism instead one
35
36 can suspend the assumption that capital is the agent of automation through which
37
38 rational and irrational modes of profit, governance and control are implemented. For
39
40 critical computation, the material, affective and cognitive evolution of automated
41
42 systems exposes the speculative dimension of reasoning embedded in the social and
43
44 collective use-meaning of information. If the automation of automation demarcates a
45
46 new threshold of transformation of AI, it is because it is involved in the
47
48 transformation of the general structuring of reasoning itself, including the triadic
49
50 configuration of abductive, inductive and abductive inferencing. If the manner in
51
52 which thought think itself thinking has always been mediated by the environment –
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3 and is thus ampliative and not representational - the formation of new hypothesis from
4
5 the increasing availability of data also defines the proliferation of non-human
6
7 intelligences. And yet, for automated reasoning to generate new hypothesis, it is
8
9 crucial that error, fallibility and indeterminacy are evaluated inductively so that they
10
11 become part of learning. Learning indeed here acquires a new meaning. It concerns
12
13 not the apprehension of notions, tasks, and functions. Instead, it requires thinking
14
15 through errors, blind spots, unknowns. Here, the possible fallibility of reasoning is
16
17 central to the possibilities of learning through hypothetical scenarios, pushing the
18
19 limits of automated cognition beyond data recombination or the mere executions of
20
21 rules.
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24
25 As Lorenzo Magnani argues, since the 80s abductive reasoning has been adopted by
26
27 diagnostic and expert systems (2009), and in general by a computational infrastructure
28
29 of reasoning, based on the use of inferential synthesis or inference to the best
30
31 explanation (68). Importantly, Magnani distinguishes between model-based
32
33 abduction— a theory based inference - and manipulative abduction – defined by
34
35 action-oriented or extra-theoretical reasoning (7; 9-12).¹⁹
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39 Theoretical or model-based abduction corresponds to the exploitation of internalised
40
41 models, diagrams or pictures and illustrates, according to Magnani, much of what is
42
43 important in creative abductive reasoning, in humans and in computational programs
44
45 (23-24; 34; 36), involving the objective of selecting and creating a set of hypotheses
46
47 (diagnoses, causes, prognosis). Theoretical abduction, according to Magnani, however
48
49 fails to account for those cases in which there is a kind of “discovering through
50
51 doing” (42); cases in which new and still unexpressed information is codified by
52
53 means of manipulations of some external objects. Manipulative abduction instead
54
55 happens with thinking through doing. It refers to extra-theoretical behavior that
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3 creates communicable accounts of new experiences and integrates them into existing
4 systems of experimental and linguistic practices (Magnani, 46).²⁰
5
6

7 In models of artificial intelligence, for instance, abductive reasoning has been used for
8 diagnosis, planning, natural languages processing, probability theory, formal
9 programming (Magnani, 5). If abduction has a logical form that is distinct from
10 deduction and induction, it is because when working computationally – and thus
11 involving a synthesis of both a new calculus and logic – the selective or creative
12 activities of this retro-active thinking (i.e. that starts from consequences to track
13 causes) involves a hypothesis generation and not simply an explanation of
14 consequences.
15
16

17 For instance, the automation of abduction includes AI computer programs such as
18 ARCHIMEDES, which represents geometrical diagrams in pixels arrays and
19 propositional statements. Here, the computer program can manipulate and modify
20 these representations and make new geometrical constructions, e.g., adding parts,
21 moving elements and components (Magnani, 159). As the program manipulates
22 specific diagrams, it also records new information and detects equivalences between
23 areas so as to connect many different methods for learning and generalizing the
24 Pythagorean theorem, by running experiments and observe the interaction between
25 diagrams. This logical manipulation proposed by the program to verify the Theorem,
26 involves the algorithmic autonomous discovery of conjunctures that contribute to the
27 construction of demonstrations, but that also indicates the role of creativity in
28 diagrammatic reasoning (160).
29
30

31 Instead of statistical calculus based on the inductive inference to a general, already
32 known rule, concept and object, that explain certain data, the goal of abduction is thus
33 “to infer extentional knowledge” (Kakas and Sadri, 2002, 405).²¹ Whilst inductive
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3 inferences is linked to statistical observations conforming to general rules and local
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5 situations, abduction instead describes the causes of observation that concern an
6
7 incomplete state, using a general theory to create new hypothesis and explain their
8
9 incompleteness.
10

11 The automation of abduction has also been specific used in logical systems aiming to
12
13 solve the problem of scheduling and planning, of optical music recognition,
14
15 information integration and software inconsistencies (Kakas, 2000). In particular, the
16
17 notion of Abductive Concept Learning has been used to discuss algorithms that
18
19 integrate “explanatory learning” (predictive) and “learning with confirming”
20
21 (descriptive), using both methods of inductive and abductive inferences in machine
22
23 learning. But what exactly would an abductive form of learning in AI imply? One
24
25 prerogative of this kind of automated abduction is that algorithms learn from
26
27 incomplete information (thus involving the activity of prediction) and are able to
28
29 classify new cases that may otherwise remain incomplete or not fully specified. Here
30
31 the condition of the incompleteness of models is a motor for speculative algorithms
32
33 that seek to learn from an incomplete background of data, whose predicates can be
34
35 both specified and unspecified (Kakas, 3).
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40 In the specific context of machine learning, abductive reasoning is used to elaborate
41
42 hypothesis in the face of incomplete information and overcome the problem of
43
44 overfitting, whereby algorithms are heuristically programmed to learning from past
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46 data and thus delimit the configuration of larger and new hypothesis to given patterns
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48 of trial and error (3-4). As opposed to other machine learning systems that deal with
49
50 incomplete information, such as for instance LINUS, the automated model of
51
52 Abductive Concept Learning, for instance, does not simply adopt methods to
53
54 complete the missing information and then learn from already completed data (4-5).
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3 This model instead engages incomplete information dynamically and thus from within
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5 the very process of learning, where abduction works not only to track data retro-
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7 actively, but also speculatively, by inventing hypothesis that can lead to new rules,
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9 axioms, truths.

10
11 The so-called “non-monotonic” (i.e., ampliative) quality of expansive reasoning in
12
13 abductive logic allows for more hypotheses to be constructed from locally-constrained
14
15 inferential practices. It tends towards a general explanation, involving a synthetic
16
17 dimension that integrates particularities through the speculative elaboration of axioms
18
19 (and thus an expansion of deductive implications).

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23 Whilst automated abduction allows algorithms to learn from incomplete information,
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25 there are also programs such as SOLAR (Inoue et al., 2013, 246) using meta-level
26
27 abduction, which is performed more generally on networks whose pathways are
28
29 incomplete, and where links and nodes are missing. Deduction, the classic inferential
30
31 model of meta-reasoning, aims to predict or track missing pathways through the laws
32
33 of logical implications. Meta-level abduction instead is a “method to discover
34
35 unknown relations from incomplete networks” (Inoue et al., 2013, 240) and involves
36
37 “predicate invention in the form of quantified hypothesis” to infer missing rules,
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39 missing facts and unknown causes (240). In other words, this meta-theoretical
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41 dimension of inferential reasoning involves abductive learning from the observation
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43 of fact or data searching/finding, but also, and importantly here, from a goal “that has
44
45 not been observed yet” (241).²² This learning through hypothetical processing may
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47 coincide with the speculative and transcendental elaboration of algorithmic retro-
48
49 duction, whereby consequences (or results) are not only tracked back to their causes
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51 (by means explanation), but are importantly also hypothesized beyond the observable
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53 as meta-abduction concern the consequences of the relations between particulars.
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3 As automated cognition has entered the realm of hypothesis-making by connecting
4 explanations between objects, objects and concepts, and concepts themselves, it has
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6
7 also re-opened the question of what it means for artificial intelligence to become
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10 general. This generality coincides not with a universal symbolic language or the
11
12 efficient functionality of increasingly fast data correlations. Instead, general artificial
13
14 intelligence involves a new sociality of logic, the hypothetical use-meaning of data,
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16 whose laws and rules are abstracted and re-engineered in the space of reason of
17
18 machine cognition.
19

20 **Coda on general artificial intelligence.**

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23 We can now conclude that the understanding of algorithmic automation in terms of
24
25 what Hayles has called nonconscious cognition may perhaps not meet this
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27 pragmaticist view of general reasoning. I have suggested that the intelligible functions
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29 of the yet rudimentary forms of conceptual mediations occurring amongst algorithmic
30
31 species and between algorithms, data, software programs, interfaces, hardware
32
33 circuits point to a speculative reinventions with computation.
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37 With Magnani, it is possible to argue for the development of a theory of computation
38
39 based on abductive manipulation, the tendency of a distributed artificial intelligence
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41 to think through automated doing. In other words, theoretical and manipulative
42
43 abductions in automated systems show an experimental gap between causal efficacy
44
45 and conceptual elaborations, demarcating a techno-sociality of thinking where the
46
47 algorithmic use-meaning of data has become the dominant externality of cognition. In
48
49 this model of abductive reasoning, it is possible to discern the conceptual
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51 infrastructure of social collective thinking from systems of automated intelligence,
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54 whose multiplication of intelligible functions implies a dynamic of calculus and logic.
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3 From this standpoint, the technocapital submption of thinking needs to be re-
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5 addressed in terms of the automation of logic, exposing both the limits of deductive
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7 reasoning and the emergence of a critical function of computation – preserving errors
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9 and inventing truths by hypothesis. This means that debates about cognitive capital
10
11 have risked confusing the crisis of rule-bounded logic with the end of reasoning and
12
13 have thus overlooks the possibility of re-theorising automation in terms abductive
14
15 inference and thus of claiming that logic is embedded in a social that includes
16
17 machines. A recuperation of Peirce's triadic system of abduction-induction-deduction
18
19 shows us that logical thinking rather involves another level of reflexivity: the capacity
20
21 of thinking about thinking, whereby logic involves a multifunctional elaboration of
22
23 hypothesis able to infer a generality of meaning from discursive and non-discursive
24
25 social practices.
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29 Thinking about thinking involves a further level of elaboration of intelligible
30
31 functions, a meta-abduction established not by a 2nd order reflection of thinking
32
33 through doing, but by the emergence of a 3rd level of abstraction, what I called, the
34
35 automation of automation.
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39 From Magnani's argument and the wider use of abduction in computation is thus
40
41 evident that automated cognition even when operating by means of hypothetical
42
43 inference cannot yet account for some key functions of reasoning, namely the know-
44
45 how skills – to say it with Wilfrid Sellars (1963, 324-6) - or the capacity to know the
46
47 rules by which its patterning functions, without having to break them down into a set
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49 of instructions. From this standpoint, the method of experimental axiomatics
50
51 developed through the scientific articulation of the incomputables is one instance of
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53 abductive logic insofar as it points to a rudimentary level of making incomputable
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55 data partially intelligible. However, as the determination of this randomness is
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3 demarcating the tendency of AI to develop beyond its rudimentary intelligible
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5 capacities, it also points to a new form of generalised socialisation of rules, abstracted
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7 from the particularity of data contexts and yet exceeding models of encoded
8
9 cognition.²³ The question of automated cognition today concerns not only the capture
10
11 of the social (and collective) qualities of thinking, but points to a general re-
12
13 structuring of reasoning as a new sociality of thinking. Automated decision-making
14
15 are conceptual inferences, where rules and laws are invented and experimentally
16
17 structured from the computational practices of data learning.
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21 This article has taken inspiration from Hayles's fictive analysis of computational
22
23 intelligences about what and how is thinking becoming in the scientific and
24
25 technological articulation of cognition. For Hayles, cognition is a dynamic or
26
27 processual doing and not simply a contemplative form of knowing. Her work has
28
29 importantly individuated the extent to which machines have co-constituted non-
30
31 conscious functions of thinking and how they have internally questioned the idealism
32
33 of axiomatic truth and disembodied reason. In particular, for Hayles non-conscious
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35 cognition is a central activity of artificial intelligences governing automated systems
36
37 today.
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41 This article has addressed this view and argued that the crisis of deductive logic in
42
43 artificial intelligence points to the emergence of an experimental axiomatics or
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45 speculative computation that forces us to re-articulate automated cognition. However,
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47 if the Scientific Image of computational logic has changed, it has also been able to
48
49 question the Manifest Image of automated reasoning, which can no longer be
50
51 explained in terms of an efficient execution of pre-established rules. Instead, the
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53 internal limits of algorithmic programming have marked the starting point for the fictive
54
55 re-articulation of the Scientific and Manifest Image of how thinking works. If for
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3 Hayles' non-conscious cognition overlaps with a form of cybernetic control based on
4
5 inductive learning, this article questions the technocapitalist subsumption of machine
6
7 thinking and the dominance of the data-driven order. Abductive reasoning offers one
8
9 possible envisioning of a general artificial intelligence that works speculatively at
10
11 various scales (human and machine) and not as a unified Scientific Image of
12
13 cognition. Critical computation thus opens up the possibility to account for a sociality
14
15 of reasoning within the computational strata, lurking beneath the seamless
16
17 acceleration of irrational decision-making.
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¹ Learning Algorithms are an evolution of genetic algorithms invented by Holland in the 1980s aiming
22 to transform data into knowledge. Algorithms are series of instructions telling a computer what to do. If
23 the simplest of algorithms is to combine two bits and can be reduced to the And, Or, and Not
24 operations, in more complex systems, we have algorithms that combine with other algorithms, forming
25 an ecosystem. Generally speaking, every algorithm has an input and an output, as data goes in the
26 machine, the algorithms execute the instructions and leads to the pre-programmed result of the
27 computation. Instead, with machine learning, data and the preprogrammed result enter the
28 computation, whilst the algorithm turns data into the result. In particular, learning algorithms make
29 other algorithms insofar as machines write their own programs. In other words, learning algorithms are
30 part of the automation of programing itself: computers now write their own programs.

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39 ² In supervised learning, example inputs and their desired outputs are given so that the machine can
40 learn a general rule able to map inputs to outputs. With unsupervised learning, algorithms are given no
41 label and are generally used to discover hidden patterns in data or learning. Reinforcement learning
42 instead involves algorithms that perform a certain task in a dynamic environment without being told
43 exactly how to behave.

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49 ³ See Katherine Hayles, *Cognition Everywhere: The Rise of the Cognitive Nonconscious and the Costs*
50 *of Consciousness*". *New Literary History* 45(2), 2014.

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60 ⁴ Hayles does not fully explain the specificities of conscious thinking. In this article, I consider the
question of conscious and nonconscious thinking as both involving a prehensive mechanism of
registering and evaluation data. I draw on Alfred N. Whitehead 's conception of prehension, which
includes a distinction between physical and conceptual abilities of recording, evaluating and selecting

information. I draw on this important distinction to argue that algorithmic thinking involves sensible and intelligible modes of processing information, which include both non-conscious and conscious cognitive abilities. Instead, as I suggest later, algorithmic cognition is yet to acquire the function of reason insofar as incomputable layers of complexity cannot be fully integrated or compressed in algorithmic states. See Alfred N. Whitehead, *Process and Reality: An Essay in Cosmology* (New York: Free Press), 1978, pp. 23 – 26.

⁵ Hayles makes reference to Stanislaw Lem’s *Summa Technologiae* to explain that non-conscious cognition involves no calculation and that complex problem can be more efficiently resolved without the hierarchies of reflexivity and consciousness (Hayles, 2014).

⁶ I draw on Alfred N. Whitehead’s discussion about the function of reason, which is constituted by at least three levels of data elaboration. The physical and conceptual levels of prehension that are common to all species at various degrees- moving from lower to higher degrees of selection, evaluation and decision. In addition to these levels, Whitehead points to the crucial function of reason in constituting a further level of abstraction, which he defines in terms of an abstract schema, involving the construction of a structure or system of relata (relations of relations or meta-relations). See Alfred N. Whitehead, *The Function of Reason* (Princeton University Press, 1929).

⁷ It is interesting here to refer to Hayles’ explanation of this distinction in her discussion of Metzinger’s epiphenomenal view of the self, William James’s idea of the self as a construct, Damasio’s purposeful consciousness etc. Her point is that consciousness comes at the cost of constant confabulations that could not operate without the non-conscious cognition. For Hayles, this more general level of non-conscious cognition across many forms of cognitive agents, including animals, humans and machines (2014).

⁸ In *How We Think*, Hayles argues that coding technologies have transformed reading and writing and fundamentally enabled perception and cognition to develop analytic skills that move through larger quantities of information. Her argument that Humanities are faced with the power of digital technology also points at how the relation with the scientific method of analysis can be productive for close reading of texts. Her effort to re-visit the relation between thinking as the fundamental grounding of the scope of the Humanities (i.e., of moving beyond mere analysis) is further complemented by her work about non-conscious cognition and her explanation that computation and in particular algorithmic

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4 procedural thinking involves non-reflexive activities and ultimately side-skips any logical requirement
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6 (Hayles 2012; 2014).

7
8 ⁹ According to American pragmatist Wilfrid Sellars, in order to articulate the relation between objects
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10 and thought beyond the assumption that the real world is directly given to us, we need to distinguish
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12 between the *manifest image of man* and the *scientific image of man*. Despite the gender-specific
13
14 reference to human being, or persons, Sellars' argument offers us a way to address the natural
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16 dimension of things and thoughts that can be explained scientifically or through a rigorous scientific
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18 method able to revise previous scientific truths in relation to the conceptual framework by which
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20 humans see themselves as part of the world. The Manifest Image indeed corresponds to a rudimentary
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22 but already conceptual framework, starting with a picturing of the condition of being human in the
23
24 world. The Manifest Image thus account for the particularity of homo sapiens to be able to experience,
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26 to think and rationally act in the world of thinking of manifest appearances. Both these images are
27
28 complex and global and do not constitute parts that sum up to a whole. Instead they are general images
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30 that give a naturalistic account of thinking of things and thinking of thoughts, whereby scientific
31
32 epistemology coincides with an enterprise in knowing nature and yet such knowledge is the
33
34 conditioning frame for the manifestation of thinking to occur and for the two images to fuse without
35
36 merging into one another. In other words, the two images belong to the same order of complexity,
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38 defining a continuity of becoming between the images or a processual discontinuity that opens up the
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40 relation between nature and culture to scales of elaborations and continuous critical reflection about the
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42 objects described, understood, and represented. From this standpoint, this article is an attempt at
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44 analyzing the scientific image of computation (and thus its epistemological description in information
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46 and computational theory) and the manifest image of computation (the tendency of algorithmic
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48 processing of information to develop hypothetical thinking and abstract information form the social use
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50 of data). See Sellars W. 'Science, Perception and Reality'. Ridgeview Publishing Company, 1963, pp.
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52 10-11. See also O'Shea, J.R. *Wilfrid Sellars: Naturalism with a Normative Turn*. Polity, 2007. See also
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54 Seibt J. "How To Naturalize Sensory Consciousness and Intentionality Within A Process Monism with
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56 Normativity Gradient: A Reading of Sellars" J. O'Shea(ed.) *Sellars and His Legacy*. Oxford University
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58 Press, 2015.
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¹⁰ See for instance, Pedro Domingo (2015) *The Master Algorithm. How the Quest for the Ultimate Learning Machine Will Remake our World*. NY, Penguin Random House, 2015; Carl Steiner, *Automate This: How Algorithms Came to Rule Our World*, NY: Penguin, 2012.

¹¹ I am referring here to research projects and computational applications emerged from the Affective Computing Group at MIT, which has devised computational skills in robotics and artificial intelligence that arise from, respond to, or influence emotions and other affective states. Amongst their research objectives are for instance, the design of modes of communicating affective-cognitive states, creating techniques that affect stress and frustrations, devising computational skills of emotional intelligence, developing personal technologies for self-awareness. See <http://affect.media.mit.edu/> (last accessed November 23rd, 2016). See Picard Rosalind W. *Affective Computing*, MIT, 2000.

¹² With the term digital philosophy, I am referring to mathematicians and theoretical physicists using the computational paradigm to describe physical and biological phenomena in nature and to develop a computational description of the mind. This approach problematically merges being and thought through computation and thus gives an algorithmic explanation to both biophysical reality and the thinking of reality. One of the most problematic assumptions in this paradigm is the view that algorithms that evolve over time (i.e. cellular automata) can compress, render or simulate the various levels of physical, biological and cultural randomness or contingencies. See Stephen Wolfram, *How Do Simple Programs Behave?* *Architectural Design* 76, (4): 34 – 37, 2002.

¹³ Hayles makes a reference to the experiment reported by Brian Massumi about the missing half second and other empirical evidence of affective states discussed by Antonio Damasio (2015).

¹⁴ I am referring specifically to the theorization of control and affective biopolitics that can be found in the work of Massumi (2015). I have written about the relation between the ecological power and the end of rationality and instead the re-articulation of logic for political ends in the article “Computational Logic and Ecological Rationality”, in *On General Ecology. The New Ecological Paradigm in the Neocybernetic Age*, Erich Horl with James Burton, London, Bloomsbury (forthcoming, 2017).

¹⁵ In the movie Terminator, Skynet AI is an artificial general intelligence that acquires self-awareness and spreads across all computers servers, mobile devices, military satellites, androids and robots with the aim of safeguarding the world by conforming to its original program code (thus implementing deductive reasoning). Instead, the Skynet AI I am referring to here, would rather be open to the

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4 contingencies and the data retrieved in the informational environment, which means that the original
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6 mandate of the code can evolve in unexpected directions.

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8 ¹⁶ If Deleuze and Guattari's notion of immanent axiomatics involve that rules have been replaced with
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10 the material performativity of behaviours, experimental axiomatics instead refers to how rules – and
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12 logic – are experimental compressions of randomness.

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14 ¹⁷ As opposed to cognitive theories of computation, according to which to compute is to cognise and
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16 thus to produce a mental map of the data gathered by the senses, and to computational theories of
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18 cognition, for which to think is a binary affair determined by pre-set sequences of logical steps, I draw
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20 on Whitehead 's notion of prehension. For Whitehead, prehensions are modes of registering data
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22 involving a sensual or physical and conceptual or non-sensuous mode of recording the external world
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24 or the impact of externalities defining the capacities of reception of an actual entity. See Alfred N.
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26 Whitehead, *Process and Reality*, 23.

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28 ¹⁸ I understand the relation between critical and speculative computation in terms of a dynamic tension
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30 between reflection and anticipation, the conceptual tracking of causality and the tendency to structure
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32 unknown information. This also involves the tension between the critical act of thinking causality or
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34 local states and the capacities of thinking to become an abstract or general function able to transcend
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36 specificities. This means that whilst Whitehead recognises that all thinking emerges from the
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38 biophysical constraints of the living, he also argues that the function of reason is to elucidate and
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40 evaluate the causes through which these can be transcended. The function of reason is not determined
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42 by the direct apprehension of experience, but is rather a function of abstraction of the particular entities
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44 involved, and crucially involves the elaboration of the general conditions of the observations that are
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46 expressible without having to make reference to particular relations. For Whitehead, the rational
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48 attainment of this condition of generality ensures that these hold for an indefinite variety of other
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50 occasions. Alfred N. Whitehead, *Science and the Modern World*, 24-25.

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52 ¹⁹ Magnani clarifies that this model of abduction involves sentential, model-based and manipulative
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54 abduction, which not only describe the practice of abductive reasoning but also can be used to enhance
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56 the development of programmes that can computationally be able to re-discover or newly discover
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58 scientific hypothesis or mathematical theorems. See Lorenzo Magnani *Abductive Cognition: The*
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60 *Epistemological and Eco-Cognitive Dimensions of Hypothetical Reasoning*. Berlin Heidelberg:

Springer-Verlag, p.2. Magnani argues that abductive reason is irreducible to the deductive method of formal logics and this is demonstrated by the undecidability result of Turing's 'halting problem', p. 69.

²⁰ Manipulative abduction also concerns particular kinds of heuristics that resort to the existence of extra-theoretical ways of thinking – thinking through doing. According to Magnani, many cognitive processes are centered on external representations that allow to create communicable accounts of new experiences ready to be integrated into previously existing systems of experimental and linguistic (theoretical) practices (2009).

²¹ Extensional knowledge is here opposed to intentional knowledge. Whilst the former concerns inferences to a current situation, the latter rather implies universality across different states. See Marc Denecker and Antonio Kakas, (2002) "Abduction in Logic Programming" in *Computational Logic: Logic Programming and Beyond*. Kakas A and Sadri F ed. Heidelberg: Springer-Verlag Berlin, 2002, 406).

²² For instance, meta-level abduction for goal finding is used in drug design and pharmacology where hypothesis are goal oriented and also for the improvement of physical techniques in musical performance in completed causal networks. See Katsumi Inoue et al. "Completing causal networks by meta-level abduction." *Machine Learning*, Springer Verlag, 91 (2), 2013, pp. 241.

²³ My point is not to dismiss the possibility of automated thinking, but to theorise how the complex layers of algorithmic elaboration of data are able to condition and revise logical conclusions, can challenge both the ideas that automation is opposed to thinking but also that automation is the same as thinking.